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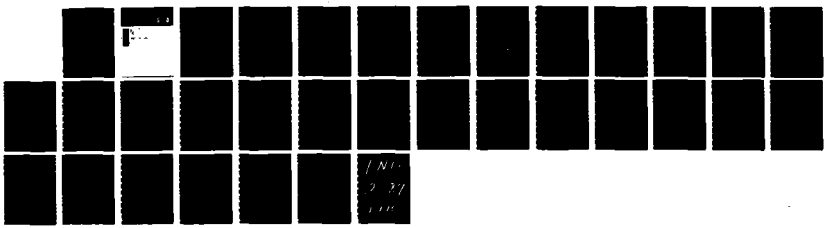

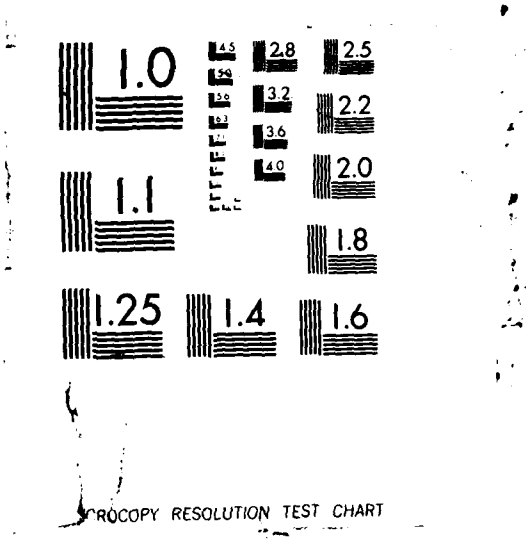
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This paper describes the Structure-Mapping Engine (SME), a cognitive simulation program for studying human analogical processing. SME is based on Gentner's Structure-Mapping theory of analogy, and provides a "tool kit" for constructing matching algorithms consistent with this theory. This flexibility enhances cognitive simulation studies by simplifying experimentation. Furthermore, SME is very efficient, making it a candidate component for machine learning systems as well. We review the Structure-Mapping theory and describe the design of the engine. Next we demonstrate some examples of its operation. Finally, we discuss our plans for using SME in cognitive simulation studies.

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Brian Falkenhainer
Qualitative Reasoning Group
Department of Computer Science

Kenneth D. Forbus
Qualitative Reasoning Group
Department of Computer Science

Dedre Gentner
Psychology Department

May 1986

Department of Computer Science
University of Illinois at Urbana-Champaign
1304 W. Springfield Avenue
Urbana, Illinois 61801

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Brian Falkenhainer
Qualitative Reasoning Group
Department of Computer Science

Kenneth D. Forbus
Qualitative Reasoning Group
Department of Computer Science

Dedre Gentner
Psychology Department

University of Illinois
1304 W. Springfield Ave
Urbana, Illinois, 61801

(217) 333–0193
Arpanet: forbus@uiuc

Abstract

This paper describes the *Structure–Mapping Engine* (SME), a cognitive simulation program for studying human analogical processing. SME is based on Gentner's *Structure–Mapping theory* of analogy, and provides a "tool kit" for constructing matching algorithms consistent with this theory. This flexibility enhances cognitive simulation studies by simplifying experimentation. Furthermore, SME is very efficient, making it a candidate component for machine learning systems as well. We review the Structure–Mapping theory and describe the design of the engine. Next we demonstrate some examples of its operation. Finally, we discuss our plans for using SME in cognitive simulation studies.

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1. Introduction

This paper describes the *Structure-Mapping Engine* (SME), a cognitive simulation program we have built to explore the computational aspects of Gentner's *Structure-Mapping theory* of analogical processing. SME is both flexible and efficient. It provides a "tool kit" for constructing matchers consistent with the kinds of comparisons sanctioned by Gentner's theory. A matcher is specified by a collection of rules. The rules can include strengths of evidence, and the program uses these weights and a novel procedure for combining the local matches constructed by the rules to efficiently produce and weigh all consistent global matches. The efficiency and flexibility of this matching algorithm suggests it would also be a viable component for machine-learning systems.

Cognitive simulation studies can offer important insights for understanding the human mind. Unfortunately, cognitive simulation programs tend to be complex and computationally expensive (c.f. [Anderson, 1983; Van Lehn, 1983]). Being complex makes the relationship between the program and the theory obscure. In addition, it is harder to make computational experiments and account for new data if the only way to change the program's operation is surgery on the code. Being computationally expensive means performing fewer experiments, and thus exploring fewer possibilities. There have been several important AI programs that study the computational aspects of analogy, but they were not designed to satisfy the above criteria (e.g. Burnstein, 1983; Winston, 1980, 1982).

The next section briefly reviews Gentner's Structure-Mapping theory. Section 3 describes SME's organization and its novel matching algorithm. Section 4 illustrates SME's operation on several examples, and Section 5 describes our plans for future development and for using it in psychological experimentation.

2. The Structure-Mapping Theory

The theoretical framework for this research is the Structure-Mapping theory of analogy (Gentner, 1980, 1982, 1983; Gentner & Gentner, 1983). This theory describes the set of implicit rules by which people interpret analogy and similarity. The central intuition is that an analogy is a mapping of knowledge from one domain (the base) into another (the target) which conveys that a system of relations known to hold in the base also holds in the target. The target objects do not have to resemble their corresponding base objects. Objects are placed in correspondence by virtue of their like roles in the common relational structure.

Given collections of objects $\{b_i\}$, $\{t_i\}$ in the base and target representations, respectively, the tacit rules for constructing the analogical mapping M can be formalized as follows:[1] Objects in the base are placed in correspondence with objects in the target:

$$M: \quad b_i \dashrightarrow t_i$$

Predicates are mapped from the base to the target according to the following mapping rules:

(1) Attributes of objects are dropped:

$$\text{e.g. } \mathrm{RED}(b_i) \not\dashrightarrow \mathrm{RED}(t_i)$$

(2) Relations between objects in the base tend to be mapped across:

$$\text{e.g. } \mathrm{COLLIDE}(b_i, b_j) \dashrightarrow \mathrm{COLLIDE}(t_i, t_j)$$

[1] Besides analogy, other kinds of similarity can be characterised by the distribution of relational and attributional predicates that are mapped. In *analogy*, only relational predicates are mapped. In *literal similarity*, both relational predicates and object-attributes are mapped. In *mere-appearance* matches, it is chiefly object-attributes that are mapped.

(3) The particular relations mapped are determined by *systematicity*, as defined by the existence of higher-order[2] constraining relations which can themselves be mapped:

e.g. CAUSE[PUSH(b_i, b_j), COLLIDE (b_j, b_k)] -->

CAUSE[PUSH(t_i, t_j), COLLIDE (t_j, t_k)]

For example, consider the analogy between heat-flow and water-flow. Figure 1 shows a water-flow situation and an analogous heat-flow situation. Figure 2 shows the representation a learner might have of these situations (simplified for clarity).

In order to comprehend the analogy "Heat is like water" a learner must:

(1) Set up the object correspondences between the two domains:
heat --> water, tube --> metal bar, beaker --> coffee, vial --> ice cube

(2) Discard object attributes, such as CYLINDRICAL(beaker).

(3) Map base relations such as
GREATER-THAN[PRESSURE(water, beaker), PRESSURE(water, vial)]
to the corresponding relations in the target domain.

(4) Observe systematicity: i.e., keep relations belonging to a systematic relational structure in preference to isolated relationships. In this example,

```
CAUSE(GREATER-THAN[PRESSURE(water, beaker),
                   PRESSURE(water, vial)],
      FLOW(water, pipe, beaker, vial))
```

is mapped into

```
CAUSE(GREATER-THAN[TEMPERATURE(heat, coffee),
                   TEMPERATURE(heat,ice cube)],
      FLOW(heat, bar, coffee, ice cube))
```

while isolated relations, such as
GREATER-THAN[DIAMETER(beaker), DIAMETER(vial)]
are discarded.

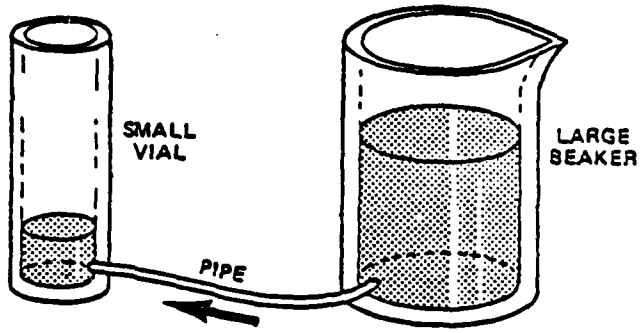
The *systematicity principle* is central to analogy. Analogy conveys a system of connected knowledge, not a mere assortment of independent facts. Prefering systems of predicates that contain higher-order relations with inferential import is a syntactic expression of this tacit preference for coherence and deductive power in analogy. It is the higher-order relational structure that determines which of two possible higher-order matches is made. For example, suppose in the previous example we were concerned with objects differing in specific heat, such as a metal ball-bearing and a marble of equal mass, rather than temperatures. Then DIAMETER becomes relevant, since (in a more complete model than we have space for) DIAMETER affects the capacity of a container, the analog to specific heat.

The Structure-Mapping theory has received a great deal of convergent theoretical support in artificial intelligence and psychology. Although there are differences in emphasis, there is widespread agreement on the basic elements of one-to-one mappings of objects with carryover of predicates (Burstein, 1983; Carbonell, 1983; Hofstadter,1984; Kedar-Cabelli, 1985; Reed, 1985;

[2] We define the *order* of an item in a representation as follows. Objects and constants are order 0. The order of a predicate is one plus the maximum of the order of its arguments. Thus GREATER-THAN(x, y) is first-order if x and y are objects, and CAUSE[GREATER-THAN(x, y), BREAK(x)] is second-order. Examples of higher-order relations include CAUSE and IMPLIES.

Figure 1a shows a water-flow situation, and Figure 1b shows an analogous heat-flow situation (adapted from Buckley, 1979, pp 15-25).

(a)



(b)

Figure 1. Two Physical Situations Involving Flow

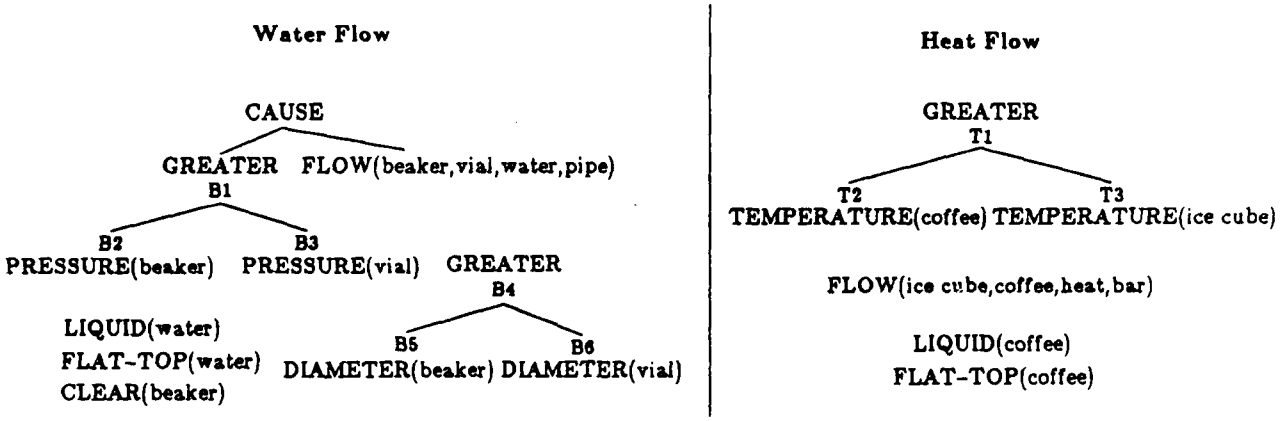


Figure 2. Simplified Water Flow and Heat Flow Descriptions

Rumelhart & Norman, 1981; Winston, 1982). Moreover, all these researchers have adopted something like the systematicity principle, or a special case of systematicity. For example, Carbonell focuses on plans and goals as the high-order relations that give constraint to a system, and Winston focuses on causality. Also, some models combine a structure-mapping component, which generates possible interpretations of a given analogy, with a pragmatic component which chooses the relevant interpretation (e.g., Burstein, 1983; Kedar-Cabelli, 1985).

Empirical psychological studies have borne out the prediction that systematicity is a key element of people's implicit rules for analogical mapping. Adults focus on shared systematic relational structure in interpreting analogy. They tend to include relations and omit attributes in their interpretations of analogy, and they judge analogies as more sound and more apt if base and target share systematic relational structure (Gentner, 1980; Gentner & Landers, 1985; Gentner & Stuart, 1983). Finally, in developmental work we have found that children are better at performing difficult mappings when the base structure is systematic (Gentner & Toupin, in press).

Given the existing theoretical and empirical psychological support, we have decided that cognitive simulation is needed to allow us to explore the theory still more deeply.

3. The Structure-Mapping Engine: Design

Given the descriptions of a base and a target, SME constructs all syntactically consistent analogical mappings between them. As noted above, the mappings consist of pairwise matches between predicates and objects in the base and target, plus a list of predicates which exist in the base but not the target. This list of predicates is the set of *candidate inferences* sanctioned by the analogy. SME also provides a syntactic evaluation of each mapping. In accordance with Structure-Mapping theory, no domain information beyond the representation of the target is used in SME to evaluate the candidate inferences - that is the job of other modules.

The base and target representations provided to SME are collections of facts called *description groups*. Domain objects and constants are collectively referred to as *entities*. The construction of the analogy is guided by *match rules* which specify which facts and entities in the base and target might match and estimate the believability of each possible component of a match. Importantly, to build a new match function one simply loads a new set of match rules. These rules are the key to SME's flexibility.

An analogy is processed in three steps. First, all potential pairings between items in the base and target are constructed and individually evaluated. Second, all sets of consistent combinations of these pairings are constructed to form the possible global matches and their corresponding candidate inference sets. Finally, the global matches are evaluated syntactically to provide a score. We now describe these computations in detail.

3.1. Step 1: Construct local match hypotheses

SME begins by finding for each entity and predicate in the base the set of entities or predicates in the target that could plausibly match that item. Plausibility is determined by *match hypothesis constructor* rules, which take the form

(MHCrule <*condition*> <*body*>)

The body of these rules is run on each pair of items (one from the base and one from the target) that satisfy the condition and installs a *match hypothesis* which represents the possibility of them matching. For example, we state that all predicates whose predicate name is identical could potentially match with the rule

```
(MHCrule (equal-functors? *base-fact* *target-fact*)
     (install-MH *base-fact* *target-fact*))
```

The likelyhood of each match hypothesis is found by running *match evidence rules* and combining their results. The evidence rules provide support for a match hypothesis by examining the syntactic properties of the items matched. For example, the rule

```
(MHErule (and (equal (mh-type *MH*) ':fact)
              (equal-functors? (mh-base-item *MH*)
                               (mh-target-item *MH*)))
         (MHevidence *MH*  0.5  0.0))
```

states "If the two items are facts and their functors are the same, then supply 0.5 evidence in favor of the match hypothesis."[3] The rules may also examine match hypotheses associated with the arguments of these items to provide support based on systematicity. This causes evidence for a match hypothesis to increase with the amount of higher-order structure supporting it. We use the Dempster-Shafer formalism for probabilities and combine evidence with a simplified form of Dempster's rule of combination (Prade, 1983; Ginsberg, 1984). By using the simplified formula we are assuming independence among the match hypotheses, but this is not a problem because we are only using it to produce scores for ordering candidates rather than estimating probabilities.

The state of the match between the water flow and heat flow descriptions of Figure 2 after running these first two sets of rules is shown in Figure 3. The weights shown in the figure are the support for each match hypothesis. Internally the program stores a Shafer interval,

[3] Evidence is attributed to a match hypothesis in the form of two numbers. The first number corresponds to evidence in favor of the match and the second number indicates evidence against the match. The sum of these numbers must be less than or equal to one.

Match Hypothesis		
Base Node	Target Node	Evidence
$GREATER_{Pressure}$	$GREATER_{Temperature}$	0.650
$GREATER_{Diameter}$	$GREATER_{Temperature}$	0.650
$PRESSURE_{beaker}$	$TEMPERATURE_{coffee}$	0.712
$PRESSURE_{vial}$	$TEMPERATURE_{ice\ cube}$	0.712
$DIAMETER_{beaker}$	$TEMPERATURE_{coffee}$	0.712
$DIAMETER_{vial}$	$TEMPERATURE_{ice\ cube}$	0.712
$FLOW_{water}$	$FLOW_{heat}$	0.790
$FLAT_{water}$	$FLAT_{coffee}$	0.790
$LIQUID_{water}$	$LIQUID_{coffee}$	0.790
vial	ice cube	0.932
beaker	coffee	0.932
water	coffee	0.864
water	heat	0.632
pipe	bar	0.632

Figure 3. Water Flow – Heat Flow Match After Running Local Rules

consisting of the support for the match and the maximum plausible support (i.e., one minus the support against it). The water flow – heat flow analogy is made possible by the program being able to match predicates with different names, such as matching PRESSURE and TEMPERATURE. This behavior is caused by the particular set of rules we are using. In these rules, relational predicates such as GREATER are limited to matching predicates having the same name, while functional predicates such as TEMPERATURE can match other functional predicates. Note that at this stage, SME is entertaining a number of matches that will later be discarded, such as LIQUID(water) ≠ LIQUID(coffee) and DIAMETER(vial) ≠ TEMPERATURE(ice cube).

2.2. Step 2: Global Match Construction and Candidate Inferences

Once the individual match hypotheses have been constructed and analyzed, SME builds a set of analogical mappings between the base and target. Each mapping is a maximal set of consistent match hypotheses plus the candidate inferences supported by those hypotheses. Consistency is enforced by insisting that a match hypothesis MH is in the analogy only if the mapping includes other match hypotheses that pair up all the arguments of the base and target items of MH. The mappings are maximal in that adding another match hypothesis would lead to a contradiction, as indicated by a base item being matched to two target items or vice versa.

The key to forming the mappings is constructing the sets of entity correspondences (called *Emaps*). Mappings are constructed in four steps. First, find all *entity justifiers*. An entity justifier is a match hypothesis that directly justifies one or more Emaps, in that some of its arguments are entities. Second, associate with each match hypothesis the set of Emaps that it

implies. This step is accomplished by propagating Emaps upwards from entity justifiers. The set of Emaps that a match hypothesis supports is simply the union of all Emaps supported by its descendents. Third, create a collection of globally consistent matches, called *Gmaps*. Call a match hypothesis that is not the descendent of any other match hypothesis a *root*. Notice that if the Emaps supported by a root are consistent, then the entire structure under it is consistent. In the simplest case, the entire collection of descendents may be collected together to form a globally consistent match. However, if the root is not consistent, then the same procedure is applied recursively to each descendent. The result is a collection of sets of match hypotheses, within which all Emaps are consistent. The final step is to generate all consistent combinations of these sets, keeping those combinations that are maximal. This is done by first combining Gmaps which are part of the same base structure (e.g. the Gmap for the pressure inequality would combine with the Gmap for the flow relation to form a single Gmap) and then making any further combinations which are consistent. Figure 4(a) shows how the initial set of Gmaps is formed, while Figure 4(b) shows the final Gmaps created for the water flow – heat flow analogy.

Associated with each Gmap is a (possibly empty) set of candidate inferences. Candidate inferences are base predicates that would fill in structure which is not in the Gmap (and hence not already in the target). In Figure 4(b), for example, Gmap #1 has the top level CAUSE predicate as its sole candidate inference. If the FLOW predicate was not present in the target, then the candidate inferences for a Gmap corresponding to the pressure inequality would be both CAUSE and FLOW. All candidate inferences must be consistent with known target facts. In addition, they must be consistent with the Gmap's structure and supported by some member of it. For example, GREATER-THAN[DIAMETER(coffee), DIAMETER(ice cube)] is not a valid candidate inference for the first Gmap because it does not intersect the existing Gmap structure.

3.3. Step 3: Global Match Selection

Several factors must be taken into account when deciding which Gmap is the best analogy. We have identified three factors as particularly important:

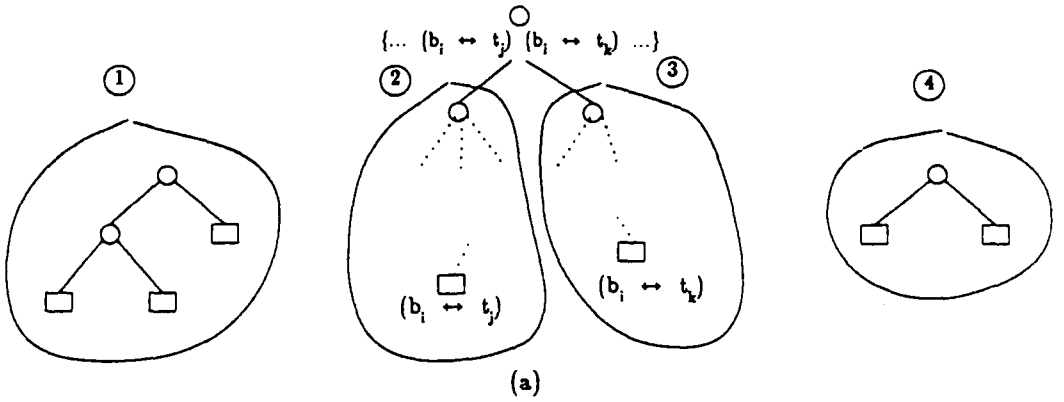
(1) The evidence for the individual match hypotheses in the Gmap.

(2) The candidate inferences sanctioned by the Gmap.

(3) The graph-theoretic structure of the Gmap, e.g., the number and relative size of connected components.

Exploring the relative importance of these and other factors is part of the desiderata for SME, hence we have made the criteria programmable. *Gmap evidence rules*, whose form is much the same as the other kinds of rules mentioned previously, can provide evidence for a Gmap based on whatever factors are deemed appropriate. To make an appropriate selection, evidence for Gmaps is combined under strict adherence to Dempster's rule for combining probabilities. Thus the set of Gmaps is treated as a set of mutually exclusive choices, and evidence in favor of one Gmap implicitly counts as evidence against the others. Dempster's rule automatically normalizes the weights so that the sum of the weights supporting each Gmap will always be less than or equal to one. In Figure 4(b), the Gmap which maps the PRESSURE relation is believed more than the Gmap which maps the DIAMETER relation. This conclusion is based on two rules. The first rule simply permits the evidence for a match hypothesis in a Gmap to count as evidence for that Gmap. The second rule gives evidence of 0.3 to a Gmap for each candidate inference it sanctions.

We suspect that the ability to "tune" the criteria for choosing a Gmap will be important for modeling individual differences in analogical style and a subject's domain knowledge. For



(a)

Gmap #1: { (GREATER$_{B1}$ ↔ GREATER$_{T1}$) (PRESSURE$_{B2}$ ↔ TEMPERATURE$_{T2}$) (PRESSURE$_{B2}$ ↔ TEMPERATURE$_{T2}$) (FLOW ↔ FLOW) }

Emaps: { (beaker ↔ coffee) (vial ↔ ice cube) (water ↔ heat) (pipe ↔ bar) }

Weight: 0.9800

Candidate Inferences: { (CAUSE GREATER$_{T1}$ FLOW) }

Gmap #2: { (GREATER$_{B4}$ ↔ GREATER$_{T1}$) (DIAMETER$_{B3}$ ↔ TEMPERATURE$_{T2}$) (DIAMETER$_{B3}$ ↔ TEMPERATURE$_{T2}$) }

Emaps: { (beaker ↔ coffee) (vial ↔ ice cube) }

Weight: 0.0195

Candidate Inferences: { }

Gmap #3: { (LIQUID ↔ LIQUID) (FLAT-TOP ↔ FLAT-TOP) }

Emaps: { (water ↔ coffee) }

Weight: 0.0004

Candidate Inferences: { }

(b)

Figure 4. Gmap Construction

example, a conservative strategy might favor taking Gmaps with some candidate inferences but not too many, in order to maximize the probability of being right.

4. Examples

The Structure–Mapping engine has been tested on a number of examples drawn from a variety of domains. We discuss a few examples to further demonstrate SME's flexibility and generality. Our first example is taken from Rutherford's analogy between the solar system and the hydrogen atom. The second example demonstrates how the program reasons about complicated descriptions of water flow and heat flow which were generated by a qualitative

reasoning program before the inception of SME.

4.1. Solar System – Rutherford Atom Analogy

The Rutherford model of the hydrogen atom was based on the well-understood behavior of the solar system. Given the descriptions shown in Figure 5, the Structure-Mapping engine constructed three possible interpretations. The most preferred mapping (given a weight of 0.99) pairs up the nucleus with the sun and the planet with the electron. This mapping is based on the mass inequality in the solar system playing the same role as the mass inequality in the atom. It sanctions the inference that the inequality, together with the mutual attraction of the nucleus and the electron, causes the electron to revolve around the nucleus. The other major Gmap (given a weight of 0.01) has the same entity correspondences, but is based on the solar system's temperature inequality mapping to the atom's mass inequality. There is much less belief in this interpretation because the temperature and mass predicates are different and because this Gmap does not allow any candidate inferences. The third Gmap is a spurious collection of match hypotheses which imply that the mass of the sun and planet should correspond to the mass of the electron and nucleus, respectively. There is no higher-level structure to support this interpretation and so the final belief is 1×10^{-6}. This example demonstrates how SME is able to generate all syntactically plausible interpretations of a potentially analogous situation. It also show that our rules have a preference for matching predicates of the same name (e.g. MASS with MASS), but is able to match predicates with different names (e.g. TEMPERATURE with MASS).

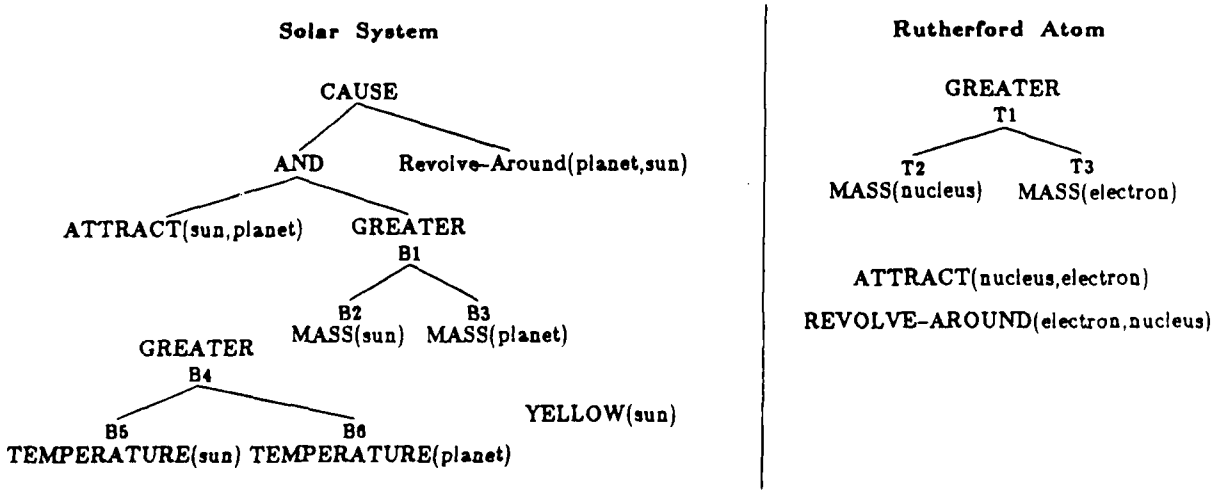


Figure 5. Solar System - Rutheford Atom Analogy

4.2. Water Flow - Heat Flow Analogy

The Structure-Mapping engine has applications beyond cognitive simulation. For example, we could use this program in conjunction with a qualitative reasoning program to model the way people use analogy to reason about the physical world. Figure 6(a) shows a domain description for water flow which was used in an actual qualitative reasoning program (Forbus 1984; Forbus & Gentner, 1983). Figure 6(b) shows a greatly reduced version of the same program's description of heat flow.

As with the earlier, simplified descriptions of water flow and heat flow, SME was able to make the correct analogical correspondences, creating all of the possible candidate inferences in the process. Interestingly, only one consistent interpretation arose. All other match hypotheses were eliminated because they had no descendants to support their existence. The candidate inferences made were the correct ones, namely that a difference in temperature and an aligned heat path implies an instance of heat flow and that the rate of heat flow between two objects is proportional to the difference in their temperatures.

4.3. Summary

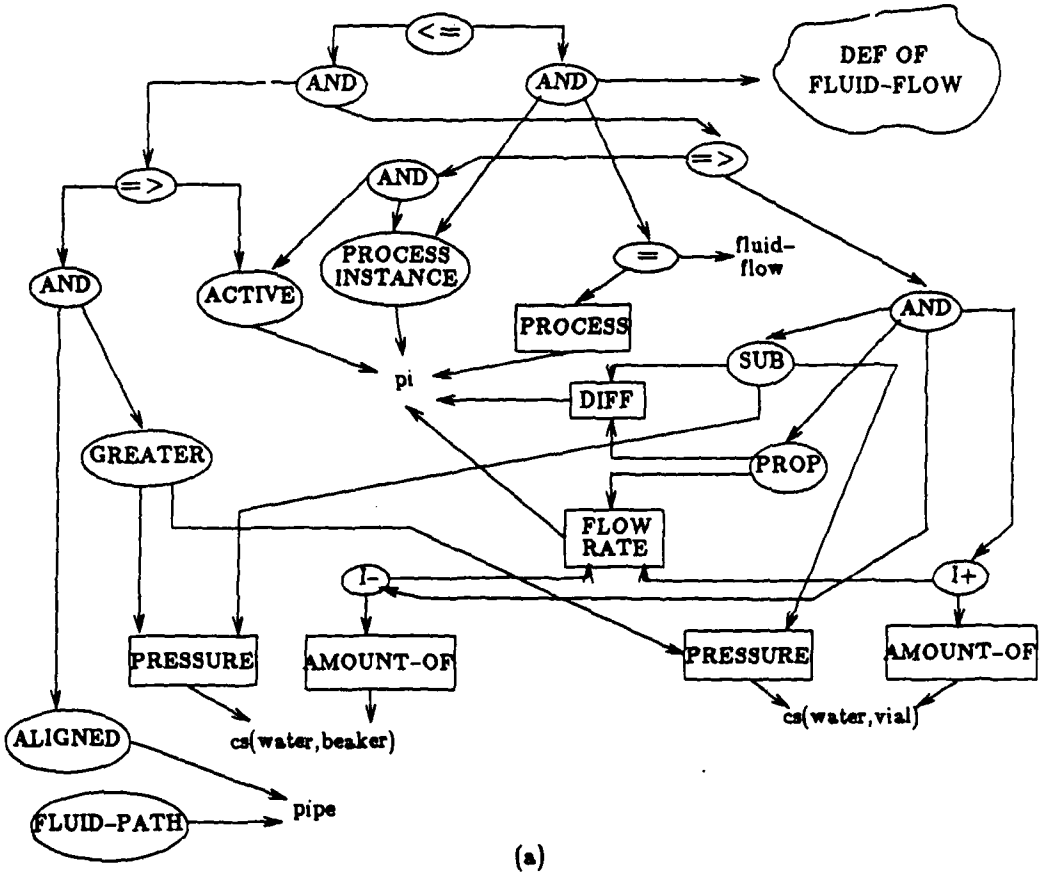
Space limitations forbid a detailed account of our experiments to date; we summarize two here. First, we have analyzed short stories described in predicate calculus to compare mere appearance, surface matches with true analogy. Second, we have begun exploring a number of match algorithms. For example, one set of rules focuses on object attributes (mere-appearance matches), thus mimicking how children tend to treat potentially analogous situations (see below). These rules, when run on the water flow - heat flow descriptions of Figure 2, choose the water to coffee correspondence as the best interpretation due to their surface similarity and fail to notice the relational structure which implies that the role of water actually corresponds to the role of heat in the water flow and heat flow situations.

5. Conclusions

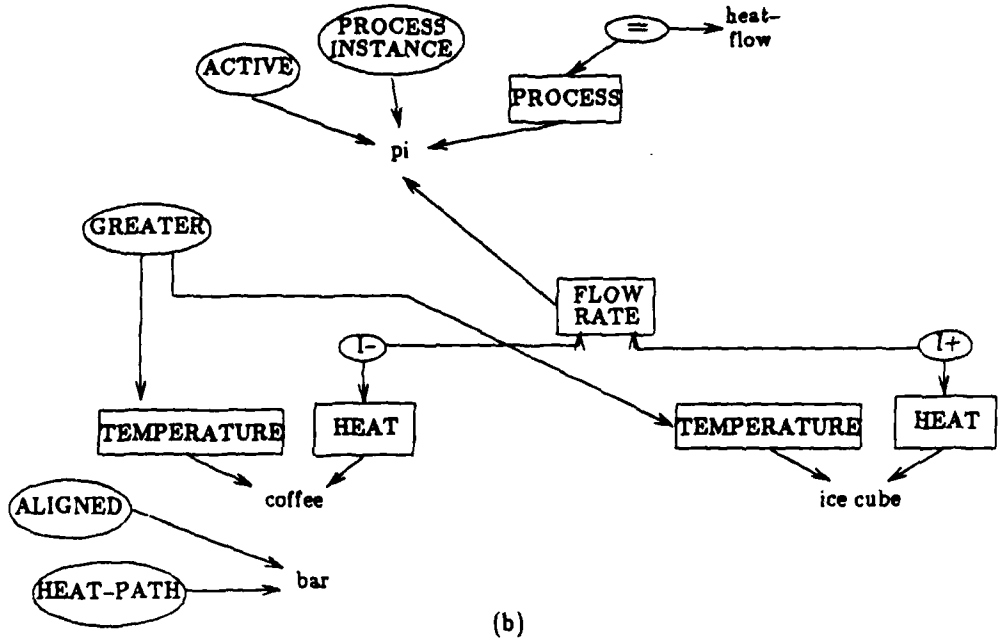
SME has significant advantages over more traditional matching algorithms. Methodologically, the advantage of producing all possible mappings is that one can easily see syntactically consistent alternatives to the best match. Yet SME's matching algorithm is very efficient, avoiding the extensive backtracking normally associated with pattern-matching systems.[4] On our large water flow - heat flow example, the program took only 0.7 seconds to perform the entire match on a Symbolics 3640. This includes everything from the construction of local match hypotheses to the gathering of candidate inferences and Gmap construction. The smaller examples average 0.4 seconds. The current program needs to be expanded to properly handle predicates which are commutative (e.g. SUM) or take a variable number of arguments (e.g. AND). In addition, we would like to add the ability to introduce new entities when required by the analogical mapping through the use of Skolem functions.

The results of SME's operation on the examples above provides suggestive evidence concerning a currently debated issue in analogy. The question concerns how much a purely syntactic account of analogy can do. Although many researchers have adopted variants of the systematicity principle, often specific domain knowledge or pragmatic information is used as well. For example, Carbonell (1981, 1983) focuses on plans and goals as the relevant higher-order relations for analogical mapping. Winston's (1982) system uses causal relations in its

[4] While we have not yet explored this possibility, it appears that a variant of this matching algorithm could be very useful for connectionist architectures.



(a)



(b)

Figure 6. Water Flow (a) and Heat Flow (b)

importance-guided matching algorithm. Winston [personal communication, November 1985] has also investigated goal-driven importance algorithms. The extreme view is taken by Holyoak (1985), whose account of analogical mapping relies solely on the relevance of predicates to the current plan. Among the claims of these researchers are (1) purely syntactic information is insufficient to guide analogical mapping and (2) even if it were sufficient, such a system would be inefficient (e.g. Burnstein, 1986, p.358). The evidence from SME so far suggests otherwise, since it generates intuitively plausible answers and does so rapidly. We intend to explore this issue more fully by using a variety of examples to see if and when the purely syntactic approach breaks down. Clearly content knowledge must be invoked at some point to evaluate whether the candidate inferences from a given analogy are appropriate. This suggests a model which uses a context-sensitive, expectation-driven system to evaluate the output of SME. This extension is compatible with the combination models proposed by Burstein (1983) and Kedar-Cabelli (1985).

In addition to tests of the basic algorithm, we plan several cognitive simulation studies of analogical reasoning and learning. We mention only one here. Psychological research shows a marked developmental shift in analogical processing. Young children rely on surface information in analogical mapping; at older ages, systematic mappings are preferred (Gentner & Stuart, 1983; Gentner & Toupin, in press; Holyoak, Juin & Billman, 1985; Vosniadou, 1985). Further, there is some evidence that a similar shift from surface to systematic mappings occurs in the novice-expert transition in adults (Chi, Glaser & Reese 1982; Larkin, 1985; Novick, 1985; Reed, 1985; and Ross, 1984).

In both cases there are two very different interpretations for this analogical shift: (1) acquisition of knowledge; or (2) a change in the analogy algorithm. The knowledge-based interpretation is that children and novices lack the necessary higher-order relational structures to guide their analogizing. The second explanation is that the algorithm for analogical mapping changes, either due to maturation or learning. In human learning it is difficult to decide this issue, since exposure to domain knowledge and practice in analogy and reasoning tend to occur simultaneously. SME gives us a unique opportunity to vary independently the analogy algorithm and the amount and kind of domain knowledge. For example, we can compare identical evaluation algorithms operating on novice versus expert representations, or we can compare different analogy evaluation rules operating on the same representation (see summary above). The performance of SME under these conditions can be compared with novice versus expert human performance.

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Appendix: Detailed Examples

A.1 Solar System – Rutherford Atom Analogy

Solar System Definition:

```
(defDescription solar-system
        entities (sun planet)
        facts  (((mass sun) :name mass-sun)
                ((mass planet) :name mass-planet)
                ((greater mass-sun mass-planet) :name >mass)
                ((attracts sun planet) :name attracts)
                ((revolve-around planet sun) :name revolve)
                ((and >mass attracts) :name and1)
                ((cause and1 revolve) :name cause-revolve)
                ((temperature sun) :name temp-sun)
                ((temperature planet) :name temp-planet)
                ((greater temp-sun temp-planet) :name >temp)))
```

Rutherford Atom Definition:

```
(defDescription rutherford-atom
        entities (nucleus electron)
        facts  (((mass nucleus) :name mass-n)
                ((mass electron) :name mass-e)
                ((greater mass-n mass-e) :name >mass)
                ((attracts nucleus electron) :name attracts)
                ((revolve-around electron nucleus) :name revolve)))
```

SME Output for Solar System - Rutherford Atom Analogy:

```
     Analogical Match from SOLAR-SYSTEM to RUTHERFORD-ATOM.

Match Hypotheses:
     [0.7900  1.0000]  (>MASS >MASS)
     [0.6500  1.0000]  (>TEMP >MASS)
     [0.5200  1.0000]  (MASS-SUN MASS-E)
     [0.5200  1.0000]  (MASS-PLANET MASS-N)
     [0.8234  1.0000]  (MASS-PLANET MASS-E)
     [0.8234  1.0000]  (MASS-SUN MASS-N)
     [0.7900  1.0000]  (ATTRACTS ATTRACTS)
     [0.7900  1.0000]  (REVOLVE REVOLVE)
     [0.7120  1.0000]  (TEMP-PLANET MASS-E)
     [0.7120  1.0000]  (TEMP-SUN MASS-N)
     [0.4160  1.0000]  (SUN ELECTRON)
     [0.4160  1.0000]  (PLANET NUCLEUS)
     [0.9801  1.0000]  (PLANET ELECTRON)
     [0.9801  1.0000]  (SUN NUCLEUS)

Gmap #0:     (MASS-PLANET MASS-N) (PLANET NUCLEUS) (SUN ELECTRON)
             (MASS-SUN MASS-E)
  Emaps: (PLANET NUCLEUS) (SUN ELECTRON)
  Weight: 0.000001
  Candidate Inferences: { }

Gmap #1:     (REVOLVE REVOLVE) (ATTRACTS ATTRACTS) (SUN NUCLEUS) (MASS-SUN MASS-N)
             (PLANET ELECTRON) (MASS-PLANET MASS-E) (>MASS >MASS)
  Emaps: (SUN NUCLEUS) (PLANET ELECTRON)
  Weight: 0.990143
  Candidate Inferences: { (CAUSE (AND >MASS ATTRACTS) REVOLVE) }

Gmap #2:     (SUN NUCLEUS) (TEMP-SUN MASS-N) (PLANET ELECTRON) (TEMP-PLANET MASS-E)
             (>TEMP >MASS)
  Emaps: (SUN NUCLEUS) (PLANET ELECTRON)
  Weight: 0.009855
  Candidate Inferences: { }
```

A.2 Water Flow - Heat Flow Analogy

Water Flow Definition:

```
(defDescription water-flow
        entities (cs-beak cs-v pipe fluid-flow pi)
        facts (((fluid-path pipe) :name fluid-path)
               ((aligned pipe) :name aligned)
               ((pressure cs-beak) :name press-beaker)
               ((pressure cs-v) :name press-vial)
               ((greater press-beaker press-vial) :name >pressure)
               ((and aligned >pressure) :name and-ap)
               ((active pi) :name active)
               ((process-instance pi) :name pi-pi)
               ((and active pi-pi) :name and-active-pi)
               ((process pi) :name process-pi)
               ((equal fluid-flow process-pi) :name process=ff)
               ((implies and-ap active) :name implies-active)
               ((diff pi) :name diff-pi)
               ((sub press-beaker press-vial diff-pi) :name sub)
               ((and pi-pi process=ff) :name and-pi-=ff)
               ((flow-rate pi) :name flow-rate)
               ((prop flow-rate diff-pi) :name prop-fr-diff)
               ((amount-of cs-beak) :name amount-beaker)
               ((amount-of cs-v) :name amount-vial)
               ((I- amount-beaker flow-rate) :name I-amount-b)
               ((I+ amount-vial flow-rate) :name I+amount-v)
               ((and sub prop-fr-diff) :name and-sub-prop)
               ((and I-amount-b I+amount-v) :name and-I+-)
               ((and and-sub-prop and-I+-) :name big-and)
               ((implies and-active-pi big-and) :name implies-aap-ba)
               ((and implies-active implies-aap-ba) :name and->active->aap-ba)
               ((implies and-pi-=ff and->active->aap-ba) :name big-implies)))
```

Heat Flow Definition:

```
(defDescription heat-flow
        entities (coffee ice-cube bar heat-flow pi)
        facts (((heat-path bar) :name heat-path)
               ((aligned bar) :name aligned)
               ((temperature coffee) :name temp-coffee)
               ((temperature ice-cube) :name temp-ice)
               ((greater temp-coffee temp-ice) :name >temp)
               ((active pi) :name active)
               ((process-instance pi) :name pi-pi)
               ((process pi) :name process-pi)
               ((equal heat-flow process-pi) :name process=hf)
               ((flow-rate pi) :name flow-rate)
               ((heat coffee) :name heat-coffee)
               ((heat ice-cube) :name heat-ice)
               ((I- heat-coffee flow-rate) :name I-hc)
               ((I+ heat-ice flow-rate) :name I+hic)))
```

SME Output for Water Flow - Heat Flow Analogy:

```
     Analogical Match from WATER-FLOW to HEAT-FLOW.

Match Hypotheses:
     [0.6500  1.0000]  (>PRESSURE >TEMP)
     [0.7900  1.0000]  (PROCESS=FF PROCESS=HF)
     [0.6500  1.0000]  (I-AMOUNT-B I-HC)
     [0.6500  1.0000]  (I+AMOUNT-V I+HIC)
     [0.7900  1.0000]  (ALIGNED ALIGNED)
     [0.7120  1.0000]  (PRESS-VIAL TEMP-ICE)
     [0.7120  1.0000]  (PRESS-BEAKER TEMP-COFFEE)
     [0.7900  1.0000]  (ACTIVE ACTIVE)
     [0.7900  1.0000]  (PI-PI PI-PI)
     [0.9227  1.0000]  (PROCESS-PI PROCESS-PI)
     [0.7120  1.0000]  (AMOUNT-BEAKER HEAT-COFFEE)
     [0.8894  1.0000]  (FLOW-RATE FLOW-RATE)
     [0.7120  1.0000]  (AMOUNT-VIAL HEAT-ICE)
     [0.6320  1.0000]  (PIPE BAR)
     [0.6320  1.0000]  (FLUID-FLOW HEAT-FLOW)
     [0.8148  1.0000]  (CS-BEAK COFFEE)
     [0.9898  1.0000]  (PI PI)
     [0.8148  1.0000]  (CS-V ICE-CUBE)

Gmap #0:     (PI-PI PI-PI) (ACTIVE ACTIVE) (ALIGNED ALIGNED) (PIPE BAR)
             (I+AMOUNT-V I+HIC) (AMOUNT-VIAL HEAT-ICE) (I-AMOUNT-B I-HC)
             (FLOW-RATE FLOW-RATE) (AMOUNT-BEAKER HEAT-COFFEE) (PROCESS=FF PROCESS=HF)
             (PROCESS-PI PROCESS-PI) (PI PI) (FLUID-FLOW HEAT-FLOW) (CS-BEAK COFFEE)
             (PRESS-BEAKER TEMP-COFFEE) (CS-V ICE-CUBE) (PRESS-VIAL TEMP-ICE)
             (>PRESSURE >TEMP)
  Emaps: (PIPE BAR) (PI PI) (FLUID-FLOW HEAT-FLOW) (CS-BEAK COFFEE) (CS-V ICE-CUBE)
  Weight: 1.000000
  Candidate Inferences:  (IMPLIES (AND PI-PI PROCESS=HF)
                             (AND (IMPLIES (AND ALIGNED >TEMP) ACTIVE)
                                  (IMPLIES (AND ACTIVE PI-PI)
                                    (AND (AND (SUB TEMP-COFFEE TEMP-ICE (DIFF PI))
                                              (PROP FLOW-RATE (DIFF PI)))
                                         (AND I-HC I+HIC)))))
```

Distribution List [Illinois/Gentner] NR 667-551

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University of Minnesota
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Dr. Beth Adelson
Dept. of Computer Science
Tufts University
Medford, MA 02155

AFOSR,
Life Sciences Directorate
Bolling Air Force Base
Washington, DC 20332

Dr Robert Ahlers
Code N711
Human Factors Laboratory
Naval Training Systems Center
Orlando, FL 32813

Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. James Anderson
Brown University
Center for Neural Science
Providence, RI 02912

Dr. John R. Anderson
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Steve Andriole
George Mason University
School of Information
Technology & Engineering
4400 University Drive
Fairfax, VA 22030

Technical Director, ARI
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Gary Aston-Jones
Department of Biology
New York University
1009 Main Bldg
Washington Square
New York, NY 10003

Dr. Patricia Baggett
University of Colorado
Department of Psychology
Box 345
Boulder, CO 80309

Dr. Eva L. Baker
UCLA Center for the Study
of Evaluation
145 Moore Hall
University of California
Los Angeles, CA 90024

Dr. Meryl S. Baker
Navy Personnel R&D Center
San Diego, CA 92152-6800

prof. dott. Bruno G. Bara
Unita di ricerca di
intelligenza artificiale
Universita di Milano
20122 Milano - via F. Sforza 23
ITALY

Dr. William M. Bart
University of Minnesota
Dept. of Educ. Psychology
330 Burton Hall
178 Pillsbury Dr., S.E.
Minneapolis, MN 55455

Leo Beltracchi
U.S. Nuclear Regulatory Comm.
Washington, D.C. 20555

Dr. Mark H. Bickhard
University of Texas
EDB 504 ED Psych
Austin, Texas 78712

Dr. Gautam Biswas
Department of Computer Science
University of South Carolina
Columbia, SC 29208

Dr. John Black
Teachers College, Columbia Univ
525 West 121st Street
New York, NY 10027

Dr. R. Darrell Bock
University of Chicago
NORC
6030 South Ellis
Chicago, IL 60637

Dr. Sue Bogner
Army Research Institute
ATTN: PERI-SF
5001 Eisenhower Avenue
Alexandrai, VA 22333-5600

Dr. Jeff Bonar
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr. Gordon H. Bower
Department of Psychology
Stanford University
Stanford, CA 94306

Dr. Robert Breaux
Code N-095R
Naval Training Systems Center
Orlando, FL 32813

Dr. Ann Brown
Center for the Study of Reading
University of Illinois
51 Gerty Drive
Champaign, IL 61280

Dr. John S. Brown
XEROX Palo Alto Research
Center
3333 Coyote Road
Palo Alto, CA 94304

Dr. Bruce Buchanan
Computer Science Department
Stanford University
Stanford, CA 94305

Maj. Hugh Burns
AFHRL/IDE
Lowry AFB, CO 80230-5000

Dr. Patricia A. Butler
OERI
555 New Jersey Ave., NW
Washington, DC 20208

Distribution List [Illinois/Gentner] NR 667-551

Dr. Joseph C. Campione
Center for the Study of Reading
University of Illinois
51 Gerty Drive
Champaign, IL 61820

Joanne Capper
Center for Research into Practice
1718 Connecticut Ave., N.W
Washington, DC 20009

Dr. Jaime Carbonell
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr Susan Carey
Harvard Graduate School of Education
337 Gutman Library
Appian Way
Cambridge, MA 02138

Dr Pat Carpenter
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

LCDR Robert Carter
Office of the Chief of Naval Operations
OP-01B
Pentagon
Washington, DC 20350-2000

Chair, Department of Psychology
College of Arts and Sciences
Catholic University of America
Washington, DC 20064

Dr Fred Chang
Navy Personnel R&D Center
Code 51
San Diego, CA 92152-6800

Dr. Davida Charney
English Department
Penn State University
University Park, PA 16802

Dr. Paul R. Chatelier
OUSDRE
Pentagon
Washington, DC 20350-2000

Dr. Michelene Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr. L. J. Chmura
Computer Science and Systems Branch
Naval Research Lab.
Washington, DC 20375-5000

Mr. Raymond E. Christal
AFHRL/MOE
Brooks AFB, TX 78235

Professor Chu Tien-Chen
Mathematics Department
National Taiwan University
Taipei, TAIWAN

Dr. Yee-Yeen Chu
Perceptronics, Inc.
21111 Erwin Street
Woodland Hills, CA 91367-3713

Dr. William Clancey
Stanford University
Knowledge Systems Laboratory
701 Welch Road, Bldg. C
Palo Alto, CA 94304

Dr. Charles Clifton
Tobin Hall
Department of Psychology
University of Massachusetts
Amherst, MA 01003

Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr Stanley Collyer
Office of Naval Technology
Code 222
800 N. Quincy Street
Arlington, VA 22217-5000

Dr. William Crano
Department of Psychology
Texas A&M University
College Station, TX 77843

Brian Dallman
3400 TTW/TTGXS
Lowry AFB, CO 80230-5000

Dr. Laura Davis
NRL/NCARAI, Code 7510
4555 Overlook Ave., SW
Washington, DC 20375-5000

Dr. Natalie Dehn
Department of Computer and Information Science
University of Oregon
Eugene, OR 97403

Dr. Gerald F DeJong
Artificial Intelligence Group
Coordinated Science Laboratory
University of Illinois
Urbana, IL 61801

Goery Delacote
Directeur de L'informatique Scientifique et Technique
CNRS
15, Quai Anatole France
75700 Paris FRANCE

Dr. Sharon Derry
Florida State University
Department of Psychology
Tallahassee, FL 32306

Dr. Andrea di Sessa
University of California
School of Education
Tolman Hall
Berkeley, CA 94720

Dr. R. K. Dismukes
Associate Director for Life Sciences
AFOSR
Bolling AFB
Washington, DC 20332

Dr Stephanie Doan
Code 6021
Naval Air Development Center
Warminster, PA 18974-5000

Distribution List [Illinois/Gentner] NR 667-551

Dr. Emanuel Donchin
University of Illinois
Department of Psychology
Champaign, IL 61820

Defense Technical
Information Center
Cameron Station, Bldg 5
Alexandria, VA 22314
Attn: TC
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Dr. Thomas M. Duffy
Communications Design Center
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Richard Duran
University of California
Santa Barbara, CA 93106

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San Diego, CA 92252

Dr. Susan Embretson
University of Kansas
Psychology Department
426 Fraser
Lawrence, KS 66045

Dr. Randy Engle
Department of Psychology
University of South Carolina
Columbia, SC 29208

Dr. Susan Epstein
Hunter College
144 S. Mountain Avenue
Montclair, NJ 07042

ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

Dr. K. Anders Ericsson
University of Colorado
Department of Psychology
Boulder, CO 80309

Dr. Jean Claude Falmagne
Department of Psychology
New York University
New York, NY 10003

Dr. Beatrice J. Farr
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Pat Federico
Code 511
NPRDC
San Diego, CA 92152-6800

Dr. Paul Feltovich
Southern Illinois University
School of Medicine
Medical Education Department
P.O. Box 3926
Springfield, IL 62708

Mr. Wallace Feurzeig
Educational Technology
Bolt Beranek & Newman
10 Moulton St.
Cambridge, MA 02238

Dr. Gerhard Fischer
University of Colorado
Department of Computer Science
Boulder, CO 80309

J. D. Fletcher
9931 Corsica Street
Vienna, VA 22180

Dr. Linda Flower
Carnegie-Mellon University
Department of English
Pittsburgh, PA 15213

Dr. Kenneth D. Forbus
University of Illinois
Department of Computer Science
1304 West Springfield Avenue
Urbana, IL 61801

Dr. Barbara A. Fox
University of Colorado
Department of Linguistics
Boulder, CO 80309

Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

Dr. Norman Frederiksen
Educational Testing Service
Princeton, NJ 08541

Dr. Michael Friendly
Psychology Department
York University
Toronto Ontario
CANADA M3J 1P3

Julie A. Gadsden
Information Technology
Applications Division
Admiralty Research Establishment
Portsdown, Portsmouth PO6 4AA
UNITED KINGDOM

Dr. Michael Genesereth
Stanford University
Computer Science Department
Stanford, CA 94305

Dr. Dedre Gentner
University of Illinois
Department of Psychology
603 E. Daniel St.
Champaign, IL 61820

Chair, Department of
Psychology
George Mason University
Fairfax, VA 22030

Chair, Department of
Psychology
Georgetown University
Wasnington, DC 20057

Dr. Robert Glaser
Learning Research
& Development Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Distribution List [Illinois/Gentner] NR 667 551

Dr Arthur M Glenberg
University of Wisconsin
W J Brogden Psychology Bldg
1202 W Johnson Street
Madison, WI 53706

Dr Sam Glucksberg
Department of Psychology
Princeton University
Princeton, NJ 08540

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University of California
Santa Barbara, CA 93106

Dr Sherrie Gott
AFHRL MODJ
Brooks AFB, TX 78235

Dr T Govindaraj
Georgia Institute of Technology
School of Industrial & Systems
Engineering
Atlanta, GA 30332

Dr Wayne Gray
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr James G Greeno
University of California
Berkeley, CA 94720

Dr Dik Gregory
Behavioral Sciences Division
Admiralty Research Establishment
Teddington, Middlesex
ENGLAND

Dr Gerhard Grossing
Atominstitut
Schuttelstrasse 115
Vienna, AUSTRIA a 1020

Prof Edward Haertel
School of Education
Stanford University
Stanford, CA 94305

Dr Henry M Halff
Halff Resources, Inc
4918 33rd Road, North
Arlington, VA 22207

Dr Ronald K Hambleton
Prof of Education & Psychology
University of Massachusetts
at Amherst
Hills House
Amherst, MA 01003

Stevan Harnad
Editor, The Behavioral and
Brain Sciences
20 Nassau Street, Suite 240
Princeton, NJ 08540

Dr Wayne Harvey
SRI International
333 Ravenswood Ave
Room B-S324
Menlo Park, CA 94025

Dr Reid Hastie
Northwestern University
Department of Psychology
Evanston, IL 60201

Prof John R Hayes
Carnegie Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr Barbara Hayes Roth
Department of Computer Science
Stanford University
Stanford, CA 95305

Dr Frederick Hayes Roth
Teknowledge
525 University Ave
Palo Alto, CA 94301

Dr Shirley Brice Heath
School of Education
Stanford University
Stanford, CA 94305

Dr Joan I Heller
505 Haddon Road
Oakland, CA 94606

Dr Jim Hollan
Intelligent Systems Group
Institute for
Cognitive Science (C-015)
UCSD
La Jolla, CA 92093

Dr Melissa Holland
Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr Keith Holyoak
University of Michigan
Human Performance Center
330 Packard Road
Ann Arbor MI 48109

Ms Julia S Hough
Lawrence Erlbaum Associates
6012 Greene Street
Philadelphia PA 19144

Dr James Howard
Dept of Psychology
Human Performance Laboratory
Catholic University of
America
Washington DC 20064

Dr Earl Hunt
Department of Psychology
University of Washington
Seattle, WA 98105

Dr Ed Hutchins
Intelligent Systems Group
Institute for
Cognitive Science (C-015)
UCSD
La Jolla, CA 92093

Dr Barbara Hutson
Virginia Tech
Graduate Center
2990 Telestar Ct
Falls Church VA 22042

Dr Barbel Inhelder
University of Geneva
Geneva SWITZERLAND 120 4

Dr. Dillon Inouye
WICAT Education Institute
Provo, UT 84057

Dr. Alice Isen
Department of Psychology
University of Maryland
Catonsville, MD 21228

Dr. Robert Jannarone
Department of Psychology
University of South Carolina
Columbia, SC 29208

Dr. Claude Janvier
Directeur, CIRADE
Universite' du Quebec a Montreal
Montreal, Quebec H3C 3P8
CANADA

Dr. Robin Jeffries
Hewlett-Packard Laboratories
P.O. Box 10490
Palo Alto, CA 94303-0971

Dr. Robert Jernigan
Decision Resource Systems
5595 Vantage Point Road
Columbia, MD 21044

Margaret Jerome
c/o Dr. Peter Chandler
83, The Drive
Hove
Sussex
UNITED KINGDOM

Chair, Department of
Psychology
The Johns Hopkins University
Baltimore, MD 21218

Dr. Douglas A. Jones
Thatcher Jones Assoc.
P.O. Box 6640
10 Trafalgar Court
Lawrenceville
NJ 08648

Dr Marcel Just
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Daniel Kahneman
The University of British Columbia
Department of Psychology
#154-2053 Main Mall
Vancouver, British Columbia
CANADA V6T 1Y7

Dr. Ruth Kanfer
University of Minnesota
Department of Psychology
Elliott Hall
75 E. River Road
Minneapolis, MN 55455

Dr. Mary Grace Kantowski
University of Florida
Mathematics Education
359 Norman Hall
Gainesville, FL 32611

Dr. Milton S. Katz
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Dr. Frank Keil
Department of Psychology
Cornell University
Ithaca, NY 14850

Dr. Wendy Kellogg
IBM T. J. Watson Research Ctr.
P.O. Box 218
Yorktown Heights, NY 10598

Dr. Dennis Kibler
University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. David Kieras
University of Michigan
Technical Communication
College of Engineering
1223 E. Engineering Building
Ann Arbor, MI 48109

Dr. Peter Kincaid
Training Analysis
& Evaluation Group
Department of the Navy
Orlando, FL 32813

Dr. Walter Kintsch
Department of Psychology
University of Colorado
Campus Box 345
Boulder, CO 80302

Dr. David Klahr
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr Mazie Knerr
Program Manager
Training Research Division
HumRRO
1100 S. Washington
Alexandria, VA 22314

Dr. Janet L. Kolodner
Georgia Institute of Technology
School of Information
& Computer Science
Atlanta, GA 30332

Dr. Stephen Kosslyn
Harvard University
1236 William James Hall
33 Kirkland St.
Cambridge, MA 02138

Dr. Kenneth Kotovsky
Department of Psychology
Community College of
Allegheny County
800 Allegheny Avenue
Pittsburgh, PA 15233

Dr. David H. Krantz
2 Washington Square Village
Apt. #15J
New York, NY 10012

Dr. Benjamin Kuipers
University of Texas at Austin
Department of Computer Sciences
T.S. Painter Hall 3.28
Austin, Texas 78712

Dr. David R. Lambert
Naval Ocean Systems Center
Code 441T
271 Catalina Boulevard
San Diego, CA 92152-6800

Distribution List [Illinois/Gentner] NR 667-551

Dr. Pat Langley
University of California
Department of Information
and Computer Science
Irvine, CA 92717

Dr. Marcy Lansman
University of North Carolina
The L. L. Thurstone Lab.
Davie Hall 013A
Chapel Hill, NC 27514

Dr. Jill Larkin
Carnegie-Mellon University
Department of Psychology
Pittsburgh, PA 15213

Dr. Jean Lave
School of Social Sciences
University of California
Irvine, CA 92717

Dr. Robert Lawler
Information Sciences, FRL
GTE Laboratories, Inc.
40 Sylvan Road
Waltham, MA 02254

Dr. Alan M. Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr Jim Levin
Dept. of Educational Psy.
210 Education Building
1310 South Sixth St.
Champaign, IL 61810-6990

Dr. John Levine
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Dr Michael Levine
Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61820

Dr. Clayton Lewis
University of Colorado
Department of Computer Science
Campus Box 430
Boulder, CO 80309

Matt Lewis
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

Library
Naval Training Systems Center
Orlando, FL 32813

Dr Jane Malin
Mail Code SR 111
NASA Johnson Space Center
Houston, TX 77058

Dr. William L. Maloy
Chief of Naval Education
and Training
Naval Air Station
Pensacola, FL 32508

Dr. Sandra P. Marshall
Dept. of Psychology
San Diego State University
San Diego, CA 92182

Dr. Manton M. Matthews
Department of Computer Science
University of South Carolina
Columbia, SC 29208

Dr. Richard E. Mayer
Department of Psychology
University of California
Santa Barbara, CA 93106

Dr. Joe McLachlan
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. James McMichael
Assistant for MPT Research,
Development, and Studies
OP 01B7
Washington, DC 20370

Dr. Barbara Means
Human Resources
Research Organization
1100 South Washington
Alexandria, VA 22314

Dr. Douglas L. Medin
Department of Psychology
University of Illinois
603 E. Daniel Street
Champaign, IL 61820

Dr. George A. Miller
Department of Psychology
Green Hall
Princeton University
Princeton, NJ 08540

Dr William Montague
NPRDC Code 13
San Diego, CA 92152-6800

Dr. Allen Munro
Behavioral Technology
Laboratories - USC
1845 S. Elena Ave., 4th Floor
Redondo Beach, CA 90277

Chair, Department of
Computer Science
U.S. Naval Academy
Annapolis, MD 21402

Dr. Allen Newell
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Richard E. Nisbett
University of Michigan
Institute for Social Research
Room 5261
Ann Arbor, MI 48109

Dr. Mary Jo Nissen
University of Minnesota
N218 Elliott Hall
Minneapolis, MN 55455

Director, Training Laboratory,
NPRDC (Code 05)
San Diego, CA 92152-6800

Distribution List [Illinois/Gentner] NR 667-551

Director, Manpower and Personnel
Laboratory,
NPRDC (Code 06)
San Diego, CA 92152-6800

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& Organizational Systems Lab,
NPRDC (Code 07)
San Diego, CA 92152-6800

Fleet Support Office,
NPRDC (Code 301)
San Diego, CA 92152-6800

Library, NPRDC
Code P201L
San Diego, CA 92152-6800

Dr. Harold F. O'Neil, Jr.
School of Education - WPH 801
Department of Educational
Psychology & Technology
University of Southern California
Los Angeles, CA 90089-0031

Dr. Michael Oberlin
Naval Training Systems Center
Code 711
Orlando, FL 32813-7100

Dr. Stellan Ohlsson
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Office of Naval Research,
Code 1133
800 N. Quincy Street
Arlington, VA 22217-5000

Office of Naval Research,
Code 1142
800 N. Quincy St.
Arlington, VA 22217-5000

Psychologist
Office of Naval Research
Branch Office, London
Box 39
FPO New York, NY 09510

Special Assistant for Marine
Corps Matters,
ONR Code 00MC
800 N. Quincy St.
Arlington, VA 22217-5000

Psychologist
Office of Naval Research
Liaison Office, Far East
APO San Francisco, CA 96503

Dr. Judith Orasanu
Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Prof. Seymour Papert
20C-109
Massachusetts Institute
of Technology
Cambridge, MA 02139

Dr. James Paulson
Department of Psychology
Portland State University
P.O. Box 751
Portland, OR 97207

Dr. Roy Pea
Bank Street College of
Education
610 W. 112th Street
New York, NY 10025

Dr. Douglas Pearse
DCIEM
Box 2000
Downsview, Ontario
CANADA

Dr. James W. Pellegrino
University of California,
Santa Barbara
Department of Psychology
Santa Barbara, CA 93106

Dr. Virginia E. Pendergrass
Code 711
Naval Training Systems Center
Orlando, FL 32813-7100

Military Assistant for Training and
Personnel Technology,
OUSD (R & E)
Room 3D129, The Pentagon
Washington, DC 20301-3080

Dr. David N. Perkins
Educational Technology Center
337 Gutman Library
Appian Way
Cambridge, MA 02138

Dr. Nancy Perry
Chief of Naval Education
and Training, Code 00A2A
Naval Station Pensacola
Pensacola, FL 32508

Department of Computer Science,
Naval Postgraduate School
Monterey, CA 93940

Dr Steven Pinker
Department of Psychology
E10-018
M.I.T.
Cambridge, MA 02139

Dr. Tjeerd Plomp
Twente University of Technology
Department of Education
P.O. Box 217
7500 AE ENSCHEDE
THE NETHERLANDS

Dr. Martha Polson
Department of Psychology
Campus Box 346
University of Colorado
Boulder, CO 80309

Dr. Peter Polson
University of Colorado
Department of Psychology
Boulder, CO 80309

Dr. Steven E. Poltrock
MCC
9430 Research Blvd.
Echelon Bldg #1
Austin, TX 78759-6509

Distribution List [Illinois/Gentner] NR 667-551

Dr. Harry E. Pople
University of Pittsburgh
Decision Systems Laboratory
1360 Scaife Hall
Pittsburgh, PA 15261

Dr. Mary C. Potter
Department of Psychology
MIT (E-10-032)
Cambridge, MA 02139

Dr. Joseph Psotka
ATTN: PERI-1C
Army Research Institute
5001 Eisenhower Ave.
Alexandria, VA 22333

Dr Lynne Reder
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. James A. Reggia
University of Maryland
School of Medicine
Department of Neurology
22 South Greene Street
Baltimore, MD 21201

Dr. Fred Reif
Physics Department
University of California
Berkeley, CA 94720

Dr Lauren Resnick
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Dr Gil Ricard
Mail Stop C04-14
Grumman Aerospace Corp.
Bethpage, NY 11714

Mark Richer
1041 Lake Street
San Francisco, CA 94118

Dr. Mary S. Riley
Program in Cognitive Science
Center for Human Information Processing
University of California
La Jolla, CA 92093

Dr. Linda G. Roberts
Science, Education, and Transportation Program
Office of Technology Assessment
Congress of the United States
Washington, DC 20510

Dr. William B. Rouse
Search Technology, Inc.
25-b Technology Park/Atlanta
Norcross, GA 30092

Dr. David Rumelhart
Center for Human Information Processing
Univ of California
La Jolla, CA 92093

Dr. Roger Schank
Yale University
Computer Science Department
P.O. Box 2158
New Haven, CT 06520

Dr. Walter Schneider
Learning R&D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

Dr. Alan H. Schoenfeld
University of California
Department of Education
Berkeley, CA 94720

Dr. Janet Schofield
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

Karen A. Schriver
Department of English
Carnegie-Mellon University
Pittsburgh, PA 15213

Dr. Judah L. Schwartz
MIT
20C-120
Cambridge, MA 02139

Dr. Marc Sebrechts
Department of Psychology
Wesleyan University
Middletown, CT 06475

Dr. Judith Segal
OERI
555 New Jersey Ave., NW
Washington, DC 20208

Dr. Sylvia A. S. Shafto
Department of Computer Science
Towson State University
Towson, MD 21204

Dr. Ben Shneiderman
Dept. of Computer Science
University of Maryland
College Park, MD 20742

Dr. Lee Shulman
Stanford University
1040 Cathcart Way
Stanford, CA 94305

Dr. Robert S. Siegler
Carnegie-Mellon University
Department of Psychology
Schenley Park
Pittsburgh, PA 15213

Dr. Derek Sleeman
Stanford University
School of Education
Stanford, CA 94305

Dr. Edward E. Smith
Bolt Beranek & Newman, Inc
50 Moulton Street
Cambridge, MA 02138

Dr. Richard E. Snow
Department of Psychology
Stanford University
Stanford, CA 94306

Distribution List [Illinois/Gentner] NR 667-551

Dr. Elliot Soloway
Yale University
Computer Science Department
P O Box 2158
New Haven, CT 06520

Dr Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Kathryn T. Spoehr
Brown University
Department of Psychology
Providence, RI 02912

Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

Dr. Albert Stevens
Bolt Beranek & Newman, Inc.
10 Moulton St
Cambridge, MA 02238

Dr. Thomas Sticht
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. John Tangney
AFOSR/NL
Bolling AFB, DC 20332

Dr Kikumi Tatsuoka
CERL
252 Engineering Research
Laboratory
Urbana, IL 61801

Dr Perry W Thorndyke
FMC Corporation
Central Engineering Labs
1185 Coleman Avenue, Box 580
Santa Clara, CA 95052

Dr Douglas Towne
Behavioral Technology Labs
1845 S Elena Ave.
Redondo Beach, CA 90277

Chair, Department of
Computer Science
Towson State University
Towson, MD 21204

Chair, Department of
Psychology
Towson State University
Towson, MD 21204

Dr. Kurt Van Lehn
Department of Psychology
Carnegie-Mellon University
Schenley Park
Pittsburgh, PA 15213

Dr. Beth Warren
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Donald Weitzman
MITRE
1820 Dolley Madison Blvd.
MacLean, VA 22102

Dr. Keith T. Wescourt
FMC Corporation
Central Engineering Labs
1185 Coleman Ave., Box 580
Santa Clara, CA 95052

Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Barbara White
Bolt Beranek & Newman, Inc.
10 Moulton Street
Cambridge, MA 02238

Dr Christopher Wickens
Department of Psychology
University of Illinois
Champaign, IL 61820

Dr Heather Wild
Naval Air Development Center
Code 6021
Warminster, PA 18974-5000

Dr. Michael Williams
IntelliCorp
1975 El Camino Real West
Mountain View, CA 94040-2216

Dr. Robert A. Wisher
U.S. Army Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Mr. John H. Wolfe
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152-6800

Dr. Joe Yasatuke
AFHRL/LRT
Lowry AFB, CO 80230

Dr. Masoud Yazdani
Dept. of Computer Science
University of Exeter
Exeter EX4 4QL
Devon, ENGLAND

Mr. Carl York
System Development Foundation
181 Lytton Avenue
Suite 210
Palo Alto, CA 94301

Dr. Joseph L. Young
Memory & Cognitive
Processes
National Science Foundation
Washington, DC 20550

END

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